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Automation technologies and their impact on employment: A review, synthesis and future research agenda

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A R T I C L E I N F O

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A B S T R A C T

This paper aims to review prior studies investigating how automation technologies affect employment. Our structured systematic review resulted in 102 publications recovered from Web of Science, Scopus and hand searching. The literature investigating how automation technologies affect employment is extremely complex and detailed, given that the impact of automation is evaluated at different levels of analysis (i.e., global, international, continental, country, regional, labour market, industry, firm, occupational, worker, and work activities) by adopting alternative methods (i.e., estimating the probability of automation or the net impact of employment) and, for some levels of analysis, the impact of each specific type of automation technology is evaluated. Moreover, the results are often inconsistent and inconclusive since only few clear results emerge and the impact of automation technologies is unclear for many levels of analysis. Research gaps and future research agenda are identified and discussed based on previous evidence.

1. Introduction

Automation technologies are technologies designed to replace "human labour input by machine input for some types of tasks within economic processes" (Sostero, 2020, p. 3). In recent years, the impact of these technologies on work has been widely discussed (Lloyd and Payne, 2019; Schlogl et al., 2021; Upchurch, 2018). In the last two decades, automation technologies such as industrial robots and artificial intelligence have improved considerably (Skrbiš and Laughland-Booÿ, 2019), allowing the performance of non-routine tasks traditionally considered feasible only by workers (Arntz et al., 2020; Frey and Osborne, 2017). As a consequence, automation technologies can replace workers in many occupations (Blanas et al., 2019), both low-skill and high-skill ones (Wajcman, 2017), and many workers may lose their jobs in the future (Spencer, 2018). Given the importance of the topic and the magnitude of the impact of automation technologies, many studies estimating their effect at various levels of analysis have emerged.

In the literature, there are five reviews and a meta-analysis that analyse the impact of technology on employment without focusing exclusively on automation. The reviews by Carnoy (1997) and Cascio and Montealegre (2016) examine how new technologies are changing work, employment (including employment conditions), and organisations. The review by Mondolo (2021) examines the impact of technological change on employment by considering the type of technology (i.e., computers and ICT, robots, automation and new digital technologies, artificial intelligence), the level of analysis (i.e., firm, sector, occupation, individual, country) and the effect on various occupational, educational and demographic groups. The review by Lyashok et al. (2020) focuses on the impact of new technologies on employment, while that by Lu and Zhou (2021) considers the impact of artificial intelligence. Finally, the meta-analysis by Dağli (2021) concludes that technology positively impacts employment with a medium overall effect size. All these studies mostly consider technological change in a general way; the review by Lu and Zhou (2021) is an exception since it focuses exclusively on a specific type of automation technology (i.e., artificial intelligence). Moreover, apart from the reviews by Carnoy (1997) and Mondolo (2021), they do not examine the effects at different levels of analysis. Considering the type of automation technology together with the level of analysis is necessary to understand the effects of automation.

In comparison to existing reviews, ours focuses on the effect of automation technologies given the huge future impact they could have in terms of employment and substitution of workers. Specifically, this review aims to answer this research question: *What is the impact of*

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automation technologies on employment at different levels of analysis? In answering this question, only automation technologies are considered. Given the definition of automation technologies provided by Sostero (2020), technologies that do not aim to replace human labour with machines are excluded from this review. Automation technologies are considered both in general (i.e., without distinguishing the type of automation technology) and, when possible, distinguishing by type (mainly industrial robots and artificial intelligence).

A structured systematic review resulted in 102 publications recovered from Web of Science, Scopus, and manual searching.

Following an inductive approach, our review presents relevant publications by distinguishing the levels of analysis considered for assessing the impact of automation technologies on employment, i.e., global, international, continental, country, regional, labour market, industry, firm, occupational, worker, and work activities. Moreover, the impact is presented by distinguishing the method applied to assess the impact and, when possible, the impact of each specific type of automation technology is presented. The simultaneous consideration of these aspects makes it possible to draw considerations that other reviews cannot reach due to the shortcomings of their analysis.

After the description and comparison of evidence from prior studies, research gaps are identified and future research avenues are suggested.

Our review contributes to the academic debate in two ways. We offer a state-of-the-art understanding of the literature about the impact of automation technologies on employment. This literature has reached sufficient maturity and a review focusing exclusively on these technologies is desirable. In this review, clarity and order are offered through a perspective of existing studies based on the levels of analysis considered, the method applied and, when possible, the impact of each specific type of automation technology. In this way, knowledge in this domain is consolidated. Moreover, we offer an agenda to advance understanding of how automation technologies affect employment by identifying major research gaps and suggesting future research avenues.

The remaining part of this paper is structured as follows. In Section 2, the methodology applied is outlined. Section 3 focuses on the results of the review, describing the methodological and empirical issues of selected publications as well as the thematic results. Finally, Section 4 is devoted to conclusions, discussion of managerial and policy implications and the offering of suggestions for future research.

2. Methodology

A structured systematic literature review was performed based on Tranfield et al. (2003). Publications were retrieved from Web of Science, Scopus, and hand searching.

Web of Science and Scopus are two well-established bibliographic databases (Caputo and Kargina, 2021) that are most used for academic and scientific research (Zhu and Liu, 2020). These two databases were used together to obtain a valid and comprehensive result given their complementary characteristics (Echchakoui, 2020; Sánchez et al., 2017).[1]

The search for relevant publications in Web of Science and Scopus was performed on 31st December 2021. The authors discussed the search strings to be considered in the final search.[2] The final search string was composed of two parts: the first considers automation technologies using *automation OR "automation technolog*" OR robot* OR "artificial intelligence" OR computeri*ation*; the second one focuses on the effect of employment using *employment OR occupation* OR job**. The use of these general terms was due to two main reasons. The first concerns keeping the research as broad as possible to avoid excluding relevant papers. The second reason is that papers on the topic do not use uniform and/or specific terms about the impact of automation technologies on employment. Search strings had to be included in the title, abstract and keywords. Emerging studies were restricted to Article and Review Articles and had to relate to one of these areas: Business, Business Finance, Economics, and Management. Only publications released since 2000 were extracted to consider only the newest automation technologies. Finally, we applied inclusion (i.e., both quantitative and qualitative studies) and exclusion criteria (i.e., publications whose abstract is not written in English) (Tshetshema and Chan, 2020).

The search in Web of Science and Scopus yielded 536 and 1058 publications, respectively. The two databases were merged and duplicates (383) were deleted by following the procedure proposed by Caputo and Kargina (2021). In this way, an initial set of 1211 publications was obtained. To identify which publications should be included in the analysis, their title and abstract were read (Moher et al., 2009). When it was not possible to reach a final decision about the inclusion, the whole text was examined. To reduce the risk of bias in the results due to the inclusion of publications that are outside the scope of the review, two authors independently performed the selection (Zupic and Čater, 2015). This process yielded a sample of 53 publications.

In addition to a search in Web of Science and Scopus, a hand searching was performed as many relevant publications on the topic are studies published by institutions, research centres and other organisations, whose publications are not included in Web of Science and Scopus. Their consideration is essential to provide an overview of the studies on the topic that would otherwise be impossible to obtain. This search yielded 49 relevant publications.

At the end of the process, a final set of 102 publications was obtained.

For each selected publication, the following information was extracted depending on how the impact of automation technologies is assessed:

- Bibliographic references (authors, year of publication, and source);
- Findings and impact on employment;
- Level of analysis (i.e., global, international, continental, country, regional, labour market, industry, firm, occupational, worker, and work activities);
- Type of automation technology (e.g., automation in general, industrial robots, artificial intelligence, and machine-based digital technologies);
- Method;
- Sample characteristics (sample size and characteristics);
- Country and year of analysis.

To identify the main thematic results, an inductive approach was adopted, i.e., we referred "to approaches that primarily use detailed readings of raw data to derive concepts, themes, or a model through interpretations made from the raw data by an evaluator or researcher" (Thomas, 2006, p. 238).

Fig. 1 shows the review process.

3. Results of the review

Before exposing the results of selected publications, the main methodological and empirical issues are discussed.

3.1. Methodological and empirical issues

3.1.1. Bibliographic references

As Fig. 2 shows, publications estimating the impact of automation on employment have grown exponentially since 2014, the year after Frey and Osborne released a preliminary version of their study about American occupations, which gave rise to an intense debate (see Frey and Osborne, 2013).

[1] Web of Science and Scopus have several advantages, such as constant update, a valuable collection of data, reliability and relevance, and inclusion of only high-impact studies (see e.g., Caputo et al., 2018; Falagas et al., 2008).

[2] In this way, the lack of a preliminary "scoping study" recommended by Tranfield et al. (2003) was addressed.

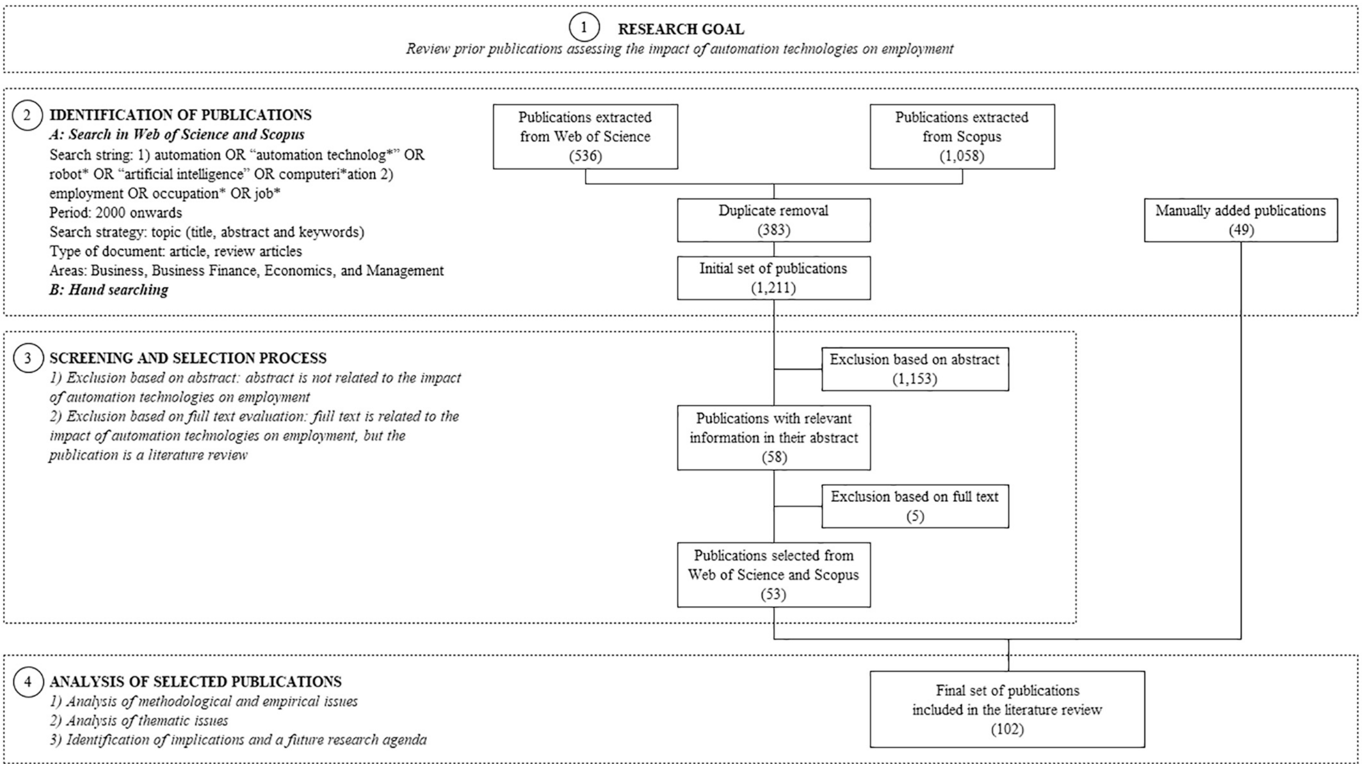

Fig. 1. Review process.

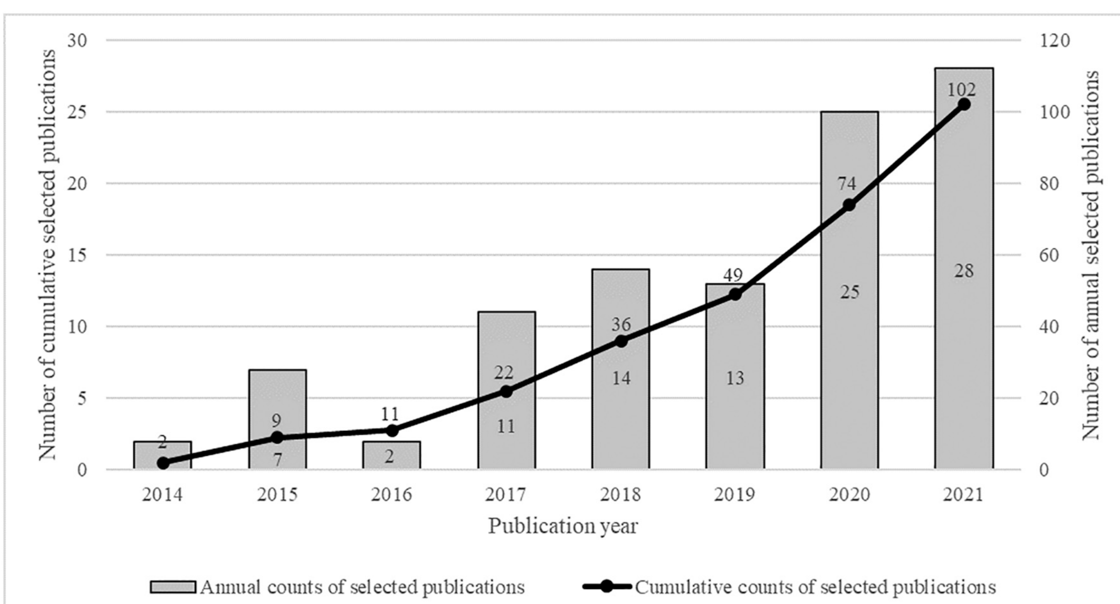

Fig. 2. Cumulative and annual counts of selected publications, updated on 31st December 2021. Source: Our elaboration.

Appendix A reports the list of sources of selected publications. No predominant source emerges, despite *Technological Forecasting and Social Change* has released 6 publications. The main sources of selected publications also include *SSRN Electronic Journal*, *European Commission*, and *Research Policy*.

3.1.2. Level of analysis

The distribution of selected publications based on the level of analysis considered is shown in Table 1. Publications estimating the impact of automation on employment tend to focus on one or two levels of analysis.

Different levels of analysis are examined, from work activities to the global level, thus highlighting the complexity of the topic. The levels of analysis that received the most attention are country, industry, occupational, and worker. Instead, the levels of analysis that received the least attention include global, international, continental, regional, and work activities.

Table 1
Levels of analysis considered in selected publications, updated on 31st December 2021.

Level of analysis	Number of publications
Distribution of selected publications by the number of levels considered	102
Publications analysing one level	*36*
Publications analysing two levels	*30*
Publications analysing three levels	*19*
Publications analysing four levels	*10*
Publications analysing five levels	*6*
*Publications not analysing any level**	*1*
Level of analysis	223
Global	*1*
International	*4*
Continental	*5*
Country	*43*
Regional	*8*
Labour market	*10*
Industry	*36*
Firm	*28*
Occupational	*38*
Worker	*45*
Work activities	*5*

Source: Our elaboration.
* The corresponding publication assesses the impact of automation technologies on employment by providing general considerations that are independent of a specific level of analysis.

3.1.3. Type of automation technology

Some publications estimate the impact of automation on employment by distinguishing the type of technology: industrial robots (considered in 41 publications) (e.g., Bonfiglioli et al., 2020; Kromann et al., 2020), automation technologies (general) (11) (e.g., Mann and Püttmann, 2018; Pellegrino et al., 2017), artificial intelligence (7) (e.g., Mutascu, 2021; Tschang and Almirall, 2021), information and communication technologies (2) (Bessen and Righi, 2019; Blanas et al., 2019), software (2) (Blanas et al., 2019; Webb, 2019), digitisation (2) (Ballestar et al., 2021; Krzywdzinski, 2021), machine-based digital technologies (1) (Balsmeier and Woerter, 2019), and other types of machines (e.g., flexible production systems, computer-aided design and manufacturing, data-driven control) (1)[3] (Camiña et al., 2020).

3.1.4. Method

To estimate the impact of automation technologies on employment, two methodologies can be adopted (Table 2): first, to estimate the probability of automation and second, to estimate the net impact on employment. Within these two methodologies, different approaches and methods can be adopted. Appendix B lists the publications that estimate the impact of automation technologies on employment, as well as the methodology adopted.

When assessing the impact of automation technologies on employment by estimating the probability of automation, occupations and tasks that are most exposed to automation are identified, their probability of automation is estimated and the risk of substitution faced by workers is assessed (Chiacchio et al., 2018). In addition, the number of workers likely to be displaced by technology is estimated (Chiacchio et al., 2018; Pouliakas, 2018). In this way, recent technological advances and technical limitations to total automation are considered (see e.g., Arntz et al., 2016; Frey and Osborne, 2017; Nedelkoska and Quintini, 2018). Two approaches can be applied in this analysis: the occupation-based approach, according to which entire occupations can be automated; the task-based approach, according to which tasks can be automated (Arntz et al., 2016). However, both or no approaches can be followed.

[3] Some of these technologies are not traditionally considered automation technologies. However, they have been considered in this review as the publication assesses the impact of automation and it was not possible to separate evidence concerning automation from that regarding other technologies.

Table 2
Methodology used in selected publications, updated on 31st December 2021.

Methodology	Number of publications
Publications estimating the probability of automation	44
Occupation-based approach	*24*
Task-based approach	*14*
Both approaches	*3*
No specific approach	*3*
Publications estimating the net impact on employment	58
Quantitative methods	*54*
Qualitative methods	*2*
Mixed methods	*2*

Source: Our elaboration.

Of the selected publications, 44 publications assess the impact of automation technologies on employment by estimating the probability of automation. Of these, 24 follow the occupation-based approach, 14 the task-based approach, 3 both approaches, and 3 do not rely on a specific approach. Within the occupation-based and task-based approaches, several estimation strategies have been proposed. The main ones are described below.

Among the publications adopting the occupation-based approach, Frey and Osborne (2017) estimated the probability of automation of occupations by following four steps: they assigned to 70 occupations the value 1 if automatable, and 0 if not based on an assessment of their automation potential with technology experts; they considered the required levels of three non-automatable capabilities (i.e., perception and manipulation, creative intelligence, and social intelligence); they estimated the probability of automation of occupations using a Gaussian process classifiers; they applied the probabilities to employment data. Many authors followed the methodology by Frey and Osborne (2017): some of them replicated it faithfully (Albuquerque et al., 2019) while others did not assess the automation potential with experts (e.g., Crowley et al., 2021; David, 2017; Durrant-Whyte et al., 2015). The results by Frey and Osborne (2017) were also used by many authors: some of them applied the probability of automation of American occupations to the employment data of other countries (e.g., Asian Development Bank, 2015; Haiss et al., 2021; Vitáloš, 2019); others performed regression analyses examining the relationship between these probabilities of automation and some labour market outcomes (Mason, 2021). In summary, publications adopting the occupation-based approach are almost exclusively based on the study by Frey and Osborne (2017).

Among the publications applying the task-based approach, three publications estimated the probability of automation of occupations based on the probability of automation of work activities and the time devoted to their performance (Chui et al., 2015, 2016; Manyika, 2017). Arntz et al. (2016) estimated the relationship between the tasks (e.g., presenting, influencing, reading professional publications and books, using a programming language) performed by workers in each American occupation and the probability of automation calculated by Frey and Osborne (2017); the relationship was then applied to other countries. Nedelkoska and Quintini (2018) replicated the methodology by Frey and Osborne (2017) using socio-demographic (e.g., education, vocational qualification) and job characteristics (e.g., wage, working hours, industry). The methodology by Nedelkoska and Quintini (2018) was followed by Foster-McGregor et al. (2021) and by Pouliakas (2018) (the latter also relied on Frey and Osborne (2017)). In summary, within the task-based approach, the applied estimation strategies vary and none predominates.

Publications applying both the occupation-based and the task-based approaches are mainly based on previous studies. Bannò et al. (2021) relied on Frey and Osborne (2017) and Nedelkoska and Quintini (2018), while Zemtsov (2017) relied on Frey and Osborne (2017), Chui et al. (2015, 2016), and Manyika (2017). Instead, Dengler and Matthes (2018) classified entire occupations into substitutable or not based on the main task (occupation-based approach) and compute the share of routine (vs. non-routine) occupations (task-based approach).

Finally, publications not adopting the occupation-based or task-based approach applied the following estimation strategies. Elliott (2017) conducted an exploratory study based on computer scientists' assessment of the possibility of machines answering certain questions in the OECD PIAAC questionnaire. Kim et al. (2017) made some simulations using Markov chains and the probabilities of automation of occupations estimated by Frey and Osborne (2017). Finally, van der Zande et al. (2019) offered some considerations based on previous literature.

In summary, most publications estimating the probability of automation adopt the occupation-based approach relying mainly on the estimation strategy and results by Frey and Osborne (2017). Alternatively, the task-based approach is applied through various estimation strategies. Few studies apply both approaches or no approach.

Instead of estimating the probability of automation, the net impact of automation on employment can be estimated (Chiacchio et al., 2018) by taking into account both the potential displacement effect and the effect of compensation mechanisms, i.e., the indirect effects (e.g., productivity effect) that emerge later and that may reduce or offset the initial substitution (see e.g., Acemoglu and Restrepo, 2020; Aghion et al., 2020a; Dauth et al., 2018). To this end, quantitative, qualitative or mixed methods can be adopted.

Of the selected publications, 58 publications assess the impact of automation technologies on employment by estimating the net impact on employment. Almost all of these publications (54 out of 58) are based on quantitative methods such as OLS regression, 2SLS regression, IV regression, fixed effects regression, shift-share IV design, method of maximum likelihood, structural equations model, and generalized method of moments. Of these, 2 publications use cross-sectional data (Ballestar et al., 2021; European Commission and Fraunhofer ISI, 2015), 52 use panel data, while one does not rely on a dataset (Tschang and Almirall, 2021). Among the 4 remaining publications, 2 adopt a qualitative method (Parschau and Hauge, 2020; Tschang and Almirall, 2021) and 2 a mixed method (Boavida and Candeias, 2021; Krzywdzinski, 2021).

3.1.5. Sample characteristics

Some publications estimate the impact of automation on employment making use of samples, consisting mainly of firms (e.g., Camiña et al., 2020; Ni and Obashi, 2021), industries and sectors (e.g., Carbonero et al., 2018; Dekle, 2020), regions (Antón et al., 2020; Chiacchio et al., 2018), commuting and employment zones (Acemoglu and Restrepo, 2020; Aghion et al., 2020a), labour markets (e.g., Caselli et al., 2021; Dottori, 2021), and occupations (Felten et al., 2019; Vermeulen et al., 2018). Other samples considered include core-based statistical areas (Leigh et al., 2020), prefectural-level cities (Du and Wei, 2021), online vacancies (Aghion et al., 2020b), workers (Borjas and Freeman, 2019), firm managers and business leaders (Parschau and Hauge, 2020), government and union representatives (Parschau and Hauge, 2020), experts in industrial productivity and employment (Boavida and Candeias, 2021), journalists (Aubert-Tarby et al., 2018), newspapers and magazines (Aubert-Tarby et al., 2018), and journal articles (Krzywdzinski, 2021).

3.1.6. Country of analysis

Table 3 reports the country of analysis considered in selected publications. One publication focuses on the global level (Manyika, 2017)[4]; 5 on the continental level (Europe) (Bowles, 2014; Foster-McGregor et al., 2021; Josten and Lordan, 2020; McGuinness et al., 2021; Pouliakas, 2018); 26 on more countries (a subset of Asian countries, a subset of European countries, OECD countries, a subset of South American countries, and developed and developing countries); one on two countries (Focacci, 2021); and 66 on one country. Most analysed countries include the United States, France, Spain, and Germany. Finally, 3 publications do not consider a specific country in their analysis (Kim et al., 2017; Tschang and Almirall, 2021; van der Zande et al., 2019).

[4] The same publication focuses on the United States.

Table 3
Country of analysis considered in selected publications, updated on 31st December 2021.

Country of analysis	Number of publications
Publications not focusing on a country*	3
Publications focusing on the global level	1
Publications focusing on the continental level (Europe)	5
Publications focusing on more countries	26
Publications focusing on two countries	1
Publications focusing on one country	66
The United States	*14*
France	*6*
Spain	*6*
Germany	*5*
China	*4*
Italy	*4*
Brazil	*3*
Canada	*3*
Japan	*3*
Mexico	*2*
South Africa	*2*
Australia	*1*
Austria	*1*
Denmark	*1*
Finland	*1*
Hungary	*1*
The Netherlands	*1*
Korea	*1*
Portugal	*1*
Russia	*1*
Singapore	*1*
Slovakia	*1*
Switzerland	*1*
Thailand	*1*
The United Kingdom	*1*

Source: Our elaboration.
* The corresponding publications assess the impact of automation technologies on employment by providing general considerations that are independent of a specific country.

3.2. Thematic results

Following an inductive approach, publications assessing the impact of automation technologies on employment were organised based on the levels of analysis considered: global, international, continental, country, regional, labour market, industry, firm, occupational, worker, and work activities. Moreover, the impact is presented by distinguishing the method applied and, when possible, the impact of each specific type of automation technology is presented. The main findings presented in this review were translated into a comprehensive framework that organises selected publications assessing the impact of automation technologies on employment (see Fig. 3).

3.2.1. Global level

3.2.1.1. Probability of automation. The publication of Manyika (2017) is the only one estimating the probability of automation at the global level. Applying the task-based approach, it emerged that by adapting existing technologies 49 % of the global work activities can be automated, of which two-thirds are carried out in four economies (China, India, Japan, and the United States), with China and India accounting together for the

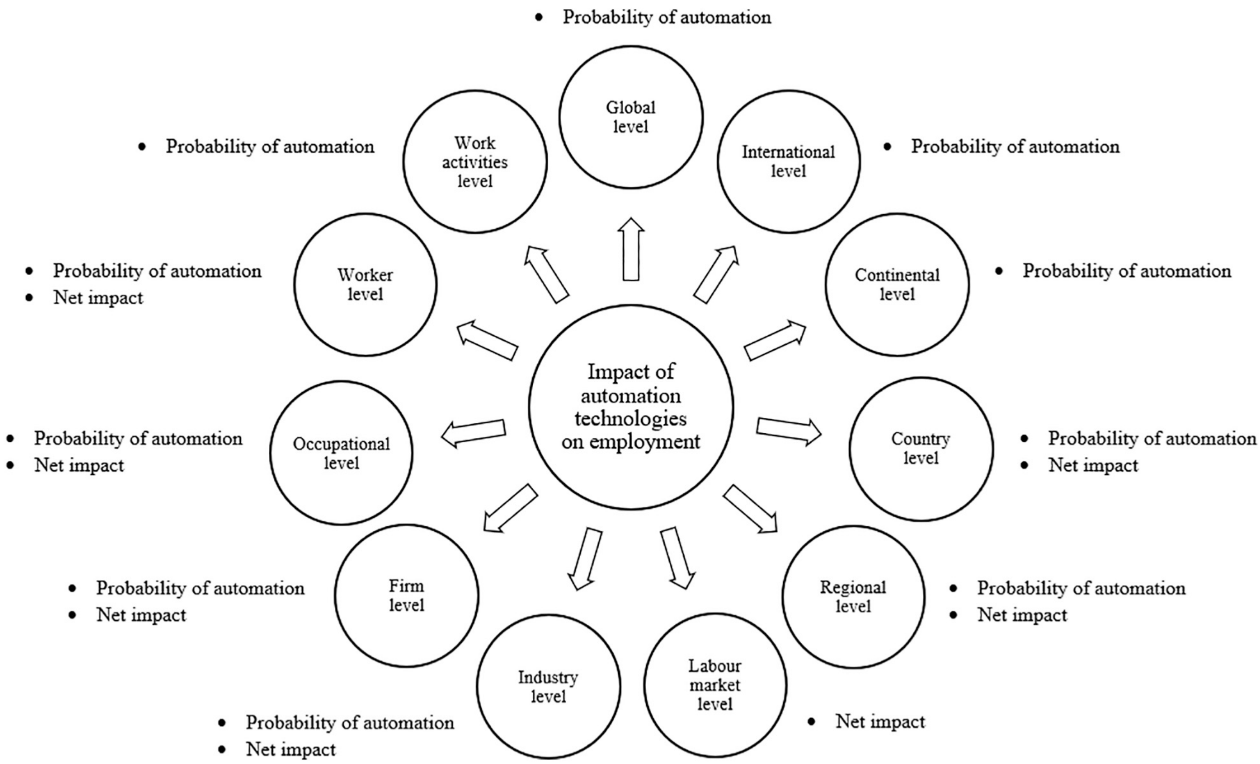

Fig. 3. Comprehensive framework for the impact of automation technologies on employment.

largest shares (Manyika, 2017). The level of technically automatable employment is also large in Europe (Manyika, 2017).

3.2.2. International level

3.2.2.1. Probability of automation. At the international level, OECD countries and ASEAN-5 (Cambodia, Indonesia, the Philippines, Thailand and Viet Nam) have been considered.

In a subset of 21 OECD countries, on average 9 % of jobs are automatable (Arntz et al., 2016). Similar results have been found by Nedelkoska and Quintini (2018), according to which in the 32 OECD countries considered, about 14 % of jobs have a probability of automation higher than 70 % and another 32 % of jobs have a probability of between 50 and 70 %. 62 % of workers in OECD countries use general cognitive skills (e.g., literacy, numeracy, and problem-solving skills) at a level that "computers are close to reproducing", while only 13 % use these skills with higher proficiency than machines (Elliott, 2017).

In ASEAN-5, 56 % of workers face a high risk of substitution and 32 % a medium risk (Chang and Huynh, 2016).

3.2.3. Continental level

3.2.3.1. Probability of automation. Europe is the only continent that has received attention in the literature. The impact of automation technologies is expected to be high. Specifically, by applying the occupation-based approach, 54 % of European workers are at risk of substitution (Bowles, 2014); instead by applying the task-based approach, only 13.9 % of workers will face a risk higher than 70 % (Pouliakas, 2018). 16 % of adult European workers have recently experienced a skills-displacing technological change, i.e., some changes in the use of technologies (e.g., machinery and ICT systems) in the last five years and as a consequence several of their skills will become outdated in the next five years (McGuinness et al., 2021). Focusing on European jobs, 47.4 % will be automatable in a decade (of which 35.2 % are fully automatable), while 40.3 % of them are not expected to be automated (Josten and Lordan, 2020). Similar results have been found by Foster-McGregor et al. (2021), according to which a percentage of jobs between 47 % and 64 % will be automatable.

3.2.4. Country level

3.2.4.1. Probability of automation. The distributions of workers based on the risk of substitution in the various countries are presented in Appendix C. Substantial national differences emerge, which are due to many factors including the type of approach adopted (i.e., occupation-based or task-based approach), the industrial and labour market structure of the countries, job tasks organisation, past investment into automation technologies, and the level of education of workers (e.g., Chang and Huynh, 2016; Foster-McGregor et al., 2021; Manyika, 2017; Pajarinen et al., 2015).

Regarding the type of approach adopted, the results obtained applying the task-based approach generally show a lower probability of automation than those deriving from the occupation-based approach (Arntz et al., 2016; Egana-delSol et al., 2021). The reason lies in the different assumptions of the two approaches. According to the occupation-based approach, entire occupations can be automated or not and the variation of tasks within occupations and their probability of automation are not taken into account (Arntz et al., 2016). This implies that most occupations have a very high or low probability of automation and few occupations have a medium probability (Arntz et al., 2016). Moreover, occupations can have a high probability of automation even if people employed in these occupations often perform tasks that are hard to automate (Arntz et al., 2016). Instead, when applying the task-based approach, the probability of automation of each task is taken into account and, as a result, few occupations have a very high or low probability of automation and most occupations have a medium probability (Arntz et al., 2016).

Focusing on OECD countries, Nedelkoska and Quintini (2018) estimate that about 30 % of the country variation in the probability of automation is due to the different structures of economic sectors, while

70 % is due to the different occupational structures within these industries. In addition, within the same occupations, job tasks organisation among countries is different; for example, the frequency of tasks that cannot be automated varies (i.e., tasks related to perception and manipulation, cognitive intelligence, and social intelligence) (Arntz et al., 2016; Nedelkoska and Quintini, 2018). The different task content of occupations reflects past investment into automation technologies and the consequent adaptation of task structure within occupations (Nedelkoska and Quintini, 2018).[5]

3.2.4.2. Net impact. When analysing the country level, it emerges that automation technologies increase employment in the long run (Autor and Salomons, 2018; Dekle, 2020; Şahin, 2020). Specifically, automation reduces employment in adopting industries, but this loss is compensated by indirect gains and increasing labour demand in customer industries (Autor and Salomons, 2018). Dekle (2020) confirms the role of industrial robots in increasing aggregate consumer demand, which in turn raises labour demand even in industries that introduce industrial robots.

On the contrary, Carbonero et al. (2018) find that industrial robots reduce worldwide employment, with a small negative effect in advanced countries and a larger one (−14 %) in developing countries. Similarly, investments in computers rise long-term unemployment (Baddeley, 2017).

According to other studies, industrial robots do not increase unemployment (Focacci, 2021) and are not labour-replacing in advanced countries (de Vries et al., 2020).

Finally, other studies conclude that the impact of automation technologies can be both positive and negative/null. Specifically, industrial robots increase total employment in developed countries, but this effect is not found in developing countries (Fu et al., 2021). Instead, the impact of artificial intelligence on unemployment seems to depend on the level of inflation: when inflation is low, it reduces unemployment if the increase in wages is offset by the creation of new jobs; when the inflation rate is high, it does not affect unemployment (Mutascu, 2021).

3.2.5. Regional level

3.2.5.1. Probability of automation. Among European regions, there is significant variation in the exposure to the probability of automation (Crowley et al., 2021). The regions that are most at risk are clustered in Eastern Europe, the Mediterranean area, and the western regions (Crowley et al., 2021).

Several factors affect the probability of automation at the regional level: occupational structure, level of unemployment, level of development, unrelated variety (i.e., level of industrial diversity), and population density (Crowley et al., 2021; Illéssy et al., 2021; Zemtsov, 2017). Regions that are specialised in the manufacturing industry, have a high level of unemployment, are least developed, have a high unrelated variety or are more populous dense face a lower risk (Crowley et al., 2021; Illéssy et al., 2021; Zemtsov, 2017). Other factors influence the probability of automation. Specifically, the innovation systems index and the proportion of men workers are associated with a higher probability of automation, while higher levels of GDP per capita reduce the risk; however, these factors lose their significance in predicting the probability of automation when sectors and occupational categories are controlled for (Crowley et al., 2021). Finally, the degree of specialisation and related variety does not affect the probability of automation at the regional level (Crowley et al., 2021).

3.2.5.2. Net impact. Industrial robots have a positive impact on regional employment (Leigh et al., 2020; Sequeira et al., 2021) as the negative displacement effects is compensated by productivity and reallocation effects when a certain level of robot penetration is reached (Sequeira et al., 2021).

However, according to other studies, industrial robots reduce employment in communing or employment zones (Acemoglu and Restrepo, 2020; Aghion et al., 2020a), with a greater effect in the manufacturing sector, more robotised industries, and routine manual (blue-collar, assembly) occupations (Acemoglu and Restrepo, 2020).

Finally, the impact of artificial intelligence may depend on the economic characteristics of the region. It creates job opportunities for middle-skilled workers in manufacturing firms operating in central China, while it causes unemployment for low-skilled workers in other regions (Xie et al., 2021).

3.2.6. Labour market level

3.2.6.1. Net impact. According to some studies, automation technologies have a positive impact on labour markets (Koch et al., 2019; Mann and Püttmann, 2018). Specifically, automation technologies reduce employment in manufacturing but increase it in the service sector, thus resulting in net job creation (Mann and Püttmann, 2018). However, labour markets with a higher percentage of workers employed in routine occupations are the ones that register the worse results (Mann and Püttmann, 2018). The adoption of industrial robots favours a net employment increase of 10 % in the four years following automation (Koch et al., 2019).

On the contrary, other studies conclude that industrial robots create a displacement effect and decrease employment (Chiacchio et al., 2018; Du and Wei, 2021; Faber, 2020). However, the dislocation caused by industrial robots only lasts in the short run and is counterbalanced by compensation mechanisms in the long run (Du and Wei, 2021).

Some authors find that industrial robots have no impact on employment (Caselli et al., 2021; Dauth et al., 2017, 2018; Dottori, 2021). This occurs even in labour markets that are specialised in highly robotised industries since the job loss in manufacturing is offset by job creation in the service sector (Dauth et al., 2017, 2018). Instead, industrial robots change the composition of aggregate employment (Dauth et al., 2017). Dottori (2021) confirms the negative impact only in the manufacturing sector and the resulting change in the composition of aggregate employment: the distribution of workers entering the labour market is modified towards industries with a lower robot intensity (Dottori, 2021).

Finally, according to Antón et al. (2020), the impact of industrial robots may be ambiguous: in European regions, it has been negative in the period 1995–2005 and positive in the following decade.

3.2.7. Industry level

3.2.7.1. Probability of automation. The probability of automation varies considerably across industries (Chang and Huynh, 2016). Moreover, the probability of automation for a particular industry differs widely across countries due to the structure of the industry in each country and its skill level of jobs (Chang and Huynh, 2016). Finally, within industries, there is considerable variation among occupations as regards their probability of automation (Manyika, 2017).

Automation mainly affects industries where predictable physical

[5] Among the possible causes explaining the difference among countries in the probability of automation, the influence of labour productivity and international trade on the probability of automation has been analysed. Labour productivity has a negative impact on this probability (Foster-McGregor et al., 2021). On the contrary, the probability of automation is increased on average by 0.5 percentage points in a situation in which a country is involved in international trade compared to a scenario in which the country was an autarky (Foster-McGregor et al., 2021). Moreover, the effects of labour productivity and trade add up: trade is more beneficial for countries with low productivity than those with high productivity in terms of reducing the probability of automation (Foster-McGregor et al., 2021).

(thus automatable) work activities are frequent (Manyika, 2017; Nedelkoska and Quintini, 2018). Industries with a high probability of automation (higher than 60 %) include: agriculture, forestry and fishing; manufacturing; construction and mining; business and financial operations (including rental, financial activities, real estate, and insurance); wholesale and retail trade; transport, storage, and post; accommodation and food services; utilities and other network services (e.g., Chui et al., 2016; Frenette and Frank, 2020; Lima et al., 2021; Minian and Martinez Monroy, 2018; Piazolo and Dogan, 2021; van der Zande et al., 2019). These industries have a higher probability of automation both in urban and rural areas (Zhou et al., 2020).

On the contrary, industries with a low probability of automation (lower than 40 %) include: education; health and social work; arts, sport and entertainment; management, business, and finance; services; public administration; public utility services (e.g., Adamczyk et al., 2021; Caravella and Menghini, 2018; Egana-delSol et al., 2021; Illéssy et al., 2021; Yamashita and Cummins, 2021).

It emerges that the service sector is generally less threatened by automation (Pajarinen et al., 2015; Pajarinen and Rouvinen, 2014), despite also some service sectors having a high probability of automation (e.g., wholesale and retail trade; accommodation and food services) (Fuei, 2017; Nedelkoska and Quintini, 2018). The higher protection of the service sector against automation is because in this sector predictable physical (thus automatable) tasks are less frequent (Manyika, 2017; Nedelkoska and Quintini, 2018). Low-wage/low-skilled sectors (e.g., transport, storage, and post) are also affected by automation technologies (Bowles, 2014).

Only Frey and Osborne (2017) try to explain how industries will be affected by automation in the future. Industries with a high probability of automation (e.g., transportation and logistics, office and administration, and production) are likely to be substituted by computer capital relatively soon (Frey and Osborne, 2017). There will then be a slowdown due to the presence of engineering bottlenecks that prevent automation and that regard perception and manipulation, creative and social intelligence (Frey and Osborne, 2017). Once the barriers regarding perception and manipulation will be overcome, the automation of industries with a medium probability of automation (e.g., installation, maintenance, and repair) will take place (Frey and Osborne, 2017). Finally, industries with a lower probability of automation (e.g., management, business, finance, education, healthcare, arts and media) will be automated once barriers related to creative and social intelligence will be resolved (Frey and Osborne, 2017).

3.2.7.2. Net impact. Automation has a positive effect on total employment at the industry level (Acemoglu et al., 2020b; Aubert-Tarby et al., 2018; Klenert et al., 2020) and thus generate productivity effects that outweigh the potential displacement effects (Acemoglu et al., 2020b). Automation increases employment only in industries that are more exposed to international trade and competition, but it has no significant impact on others (Acemoglu et al., 2020b). Focusing on industrial robots, one additional robot per 1000 workers increases total industrial employment by 1.31 %, which corresponds to 5 additional workers (Klenert et al., 2020). Finally, in the press industry, digitisation increases the probability of job creation and reduces the risk of job destruction (Aubert-Tarby et al., 2018).

On the contrary, other studies find that industrial robots and software destroy jobs in the industry where they are adopted (Acemoglu et al., 2020b; Borjas and Freeman, 2019; Compagnucci et al., 2019; Webb, 2019). Acemoglu et al. (2020b) specify that, while industrial robots decrease employment at the industry level, their impact on firms is different: adopting firms increase their employment and reduce their costs at the expense of competitors, which experience a decline in employment.

According to other studies, automation technologies may not affect employment in the industry (e.g., Graetz and Michaels, 2018; Kromann et al., 2020; Krzywdzinski, 2021). Automation and artificial intelligence have employment implications in terms of changing work organisations instead of worker substitution (Boavida and Candeias, 2021). Artificial intelligence has no hiring effects at the industry level, maybe because its effects have not materialised yet, despite its ability to substitute workers in some tasks (Acemoglu et al., 2020a).

Finally, some studies conclude that the impact of automation technologies may depend on the industry. Automation reduces employment in the manufacturing sector (the sub-sector "wood products and furniture" is the only exception), while it increases employment in most service industries (Mann and Püttmann, 2018). According to Vermeulen et al. (2018), automation destroys jobs in "applying" sectors (e.g., production; office and administrative support; transportation and material moving), while it favours job creation in "making" sectors (i.e., sectors that develop, produce, supply and support the use of automation technologies) and in complementary sectors (i.e., sectors that facilitate or inhibit the exploitation of automation). Artificial intelligence increases skill demand in medium-tech industries, but not in low-tech ones (Xie et al., 2021).

3.2.8. Firm level

3.2.8.1. Probability of automation. Firm characteristics that have been considered in the literature include firm size, sector, and technology adoption.

The effect of firm size on the risk of substitution faced by workers is not clear. In Brazil and Canada, the probability of automation decreases as firm size increases (Frenette and Frank, 2020; Lima et al., 2021). On the contrary, in European countries and the United Kingdom, jobs with a high probability of automation tend to be in larger and single-site firms (Pouliakas, 2018). European workers experiencing skills-displacing technological change tend to be employed in large firms (McGuinness et al., 2021).

Workers facing a high risk of substitution or skills-displacing technological change tend to be employed in the private sector (McGuinness et al., 2021; Pouliakas, 2018).

Finally, workers employed in firms that can be early adopters of new technologies face a higher risk of substitution (Chang and Huynh, 2016).

3.2.8.2. Net impact. According to some studies, automation has a positive impact on employment at the firm level (Aghion et al., 2020b; Aubert-Tarby et al., 2018; Bessen et al., 2020; Domini et al., 2021). Automating firms have higher employment and experience higher employment growth overall than firms that do not automate (Bessen et al., 2020). However, after the introduction of automation technologies, the level of employment in automating firms is smaller and employment growth is slower (Bessen et al., 2020). On the contrary, other studies find that firms experience employment growth both before and after the introduction of automation technologies, with no relevant changes in the workforce composition (Domini et al., 2021). The positive impact of automation technologies is confirmed since their introduction decreases the risk of job loss in larger firms and firms with higher digitisation intensity (Aubert-Tarby et al., 2018). The positive effect also concerns unskilled industrial workers and is obtained thanks to productivity gains, lower consumer prices, and higher sales (Aghion et al., 2020b).

Industrial robots are associated with higher employment at the firm level (Acemoglu et al., 2020b; Ballestar et al., 2020; Balsmeier and Woerter, 2019; Camiña et al., 2020; Dixon et al., 2019, 2021; Stapleton and Webb, 2020). The increase in employment occurs from the first year of adoption (Dixon et al., 2021) and also regards the firm's main affiliate (Stapleton and Webb, 2020). According to some authors, the expected increase is large (Stapleton and Webb, 2020); for others it is small (Dixon et al., 2021). These positive results are due to the complementarity between robots and human capital (Camiña et al., 2020).

Moreover, market-level spillovers and higher firm productivity lead to a reallocation of output and labour in favour of those firms that, thanks to the introduction of robots, can reduce their costs compared to their competitors (Acemoglu et al., 2020b). Despite these positive effects regarding output and costs,[6] firms that introduce robots need to invest in training since robots change the nature of work and require different employee skills (Dixon et al., 2019). Investments in robotics also increase employee turnover and reduce managerial employment (Dixon et al., 2019).

Investments in information technologies, including artificial intelligence and big data, have a small positive impact on employment (7 %) and this growth is smaller or negative in mature industries (Bessen and Righi, 2019).

According to other authors, industrial robots decrease employment at the firm level (Ballestar et al., 2021; Bonfiglioli et al., 2020; Jung and Lim, 2020; Ni and Obashi, 2021). Specifically, industrial robots inhibit employment growth; however, since they increase hourly compensation, the impact on labour may not be negative (Jung and Lim, 2020). The import of industrial robots occurs after periods of expansion in size and causes an increase in efficiency and a decline in demand for labour (Bonfiglioli et al., 2020). This decline occurs despite shocks in demand leading to firm expansion (Bonfiglioli et al., 2020).

On the contrary, some studies conclude that automation does not impact employment at the firm level (European Commission and Fraunhofer ISI, 2015; Parschau and Hauge, 2020). The overall effect is expected to be negligible also in the future (Parschau and Hauge, 2020). However, in some cases, automation increases employment thanks to higher firm productivity (Parschau and Hauge, 2020). Focusing on industrial robots, their use in manufacturing firms seems to have a neutral or slightly positive effect despite the positive impact on labour productivity and the efficiency of operations (European Commission and Fraunhofer ISI, 2015).

Instead, some studies note that the impact of industrial robots may depend on firm characteristics: adopting firm or not, firm size, capital- or labour-intensive firm (Acemoglu et al., 2020b; Koch et al., 2019; Ni and Obashi, 2021; Pellegrino et al., 2017; Tang et al., 2021). Increasing the use of robots reduces employment only in firms that do not adopt them since there is a productivity-enhancing reallocation of labour from non-adopting firms to adopting ones and the latter are larger and grow faster (Acemoglu et al., 2020b; Koch et al., 2019). Adopting and non-adopting firms, while having similar employment trends before the introduction of robots, start to diverge thereafter with adopting firms experiencing greater changes in the workforce composition (Tang et al., 2021). Regarding firm size, investment in innovative machines and equipment has no impact in general and a negative impact only in SMEs (Pellegrino et al., 2017). Instead, according to Ni and Obashi (2021), large firms and labour-intensive firms experience a negative (but not significant) impact on employment; the impact for small firms is mixed.

At the plant level, automation has a positive impact on employment (Aghion et al., 2020b). However, artificial intelligence seems to reduce hiring (Acemoglu et al., 2020a).

3.2.9. Occupational level

3.2.9.1. Probability of automation. Many occupations are potentially automatable but to varying extents (Jithitikulchai, 2020) and will be affected by the automation of work activities (van der Zande et al., 2019). In the United States, while 60 % of occupations are composed of more than 30 % of work activities that can be automated, fewer than 5 % of occupations can be completely automated (Chui et al., 2015). In Germany, for almost all occupational groups the minimum substitution potential is 0 % (i.e., there is at least one occupation that cannot be automated) while the maximum substitution potential is 100 % (i.e., there is at least one occupation that can be entirely automated) (Dengler and Matthes, 2018).

Occupations with a high probability of automation include: production and other manufacturing labourers; clerks and secretaries; bank tellers; postal, delivery and warehouse occupations; shop assistants; craft and trades occupations; food service occupations; domestic helpers and cleaners; vehicle drivers; other elementary/unskilled occupations (e.g., Brzeski and Burk, 2015; Fuei, 2017; Haiss et al., 2021; Lima et al., 2021; Pajarinen and Rouvinen, 2014). These occupations are likely to be performed by computers relatively soon and are “potentially automatable over some unspecified number of years, perhaps a decade or two” (Frey and Osborne, 2017). Instead, occupations with a low probability of automation include: science and engineering professionals; managers and administrators; academics; occupations in education; professions in personal service; hairdressers, barbers and beauticians; nurses; police and traffic officers; electricians; technicians; occupations in culture (e.g., Frenette and Frank, 2020; Haldane, 2015; le Roux, 2018; Pouliakas, 2018).

Occupations with a low probability of automation are composed of non-routine work activities that require abilities such as perception and manipulation, manual dexterity, non-routine or analytic thinking, creativity and imagination, social intelligence, comprehension, cooperation with people, influence of people, and specialised knowledge (Arntz et al., 2016; Caravella and Menghini, 2018; David, 2017; Durrant-Whyte et al., 2015; Jithitikulchai, 2020; Lee et al., 2020). These abilities can decrease the probability of automation to a significant extent: the probability decreases by 11 % when manual skills and perception are important, by 19 % when creativity is necessary, and by 15 % when social intelligence skills are required (Caravella and Menghini, 2018). On the contrary, occupations with a high probability are characterised by routine and standardised (thus automatable) work activities such as the exchange of information, selling, and use of fingers and hands (Arntz et al., 2016; Caravella and Menghini, 2018; David, 2017; van der Zande et al., 2019).

Considering the probability of automation of each occupation and the associated education and salary, it emerges that the probability of automation decreases moving from low-skill and low-wage occupations to high-skill and high-wage occupations (e.g., Adamczyk et al., 2021; Dengler and Matthes, 2018; Jithitikulchai, 2020). The reason is that more educated workers typically perform fewer automatable tasks than less educated workers (Arntz et al., 2016). However, also in some high-wage occupations, many work activities can be automated (e.g., physicists, financial planners) as well as there are low-wage occupations in which only a few work activities are automatable (e.g., maintenance workers) (Chui et al., 2015).

3.2.9.2. Net impact. According to some studies, industrial robots and artificial intelligence have no impact at the occupational level (Acemoglu et al., 2020a; Caselli et al., 2021). In the case of robots, this holds even in exposed occupations (Caselli et al., 2021).

On the contrary, other studies conclude that automation affects occupations in a way that depends on the type of technology (de Vries et al., 2020; Felten et al., 2019; Vermeulen et al., 2018; Webb, 2019). Specifically, industrial robots decrease the routine employment share (especially for manual routine jobs), while they increase the share of non-routine analytic or manual occupations (de Vries et al., 2020; Webb, 2019). The adoption of industrial robots leads to a reduction in the number of managers in the firm, while the number of non-managerial workers increases (Dixon et al., 2019, 2021). Among non-managerial workers, production (low-skilled) workers are dismissed, tech (high-skilled) workers are hired, and administrative workers are not affected (Humlum, 2019; Stapleton and Webb, 2020; Xie et al., 2021). Softwares mainly affect occupations that involve information processing based on

[6] It should be noted that robot adoption is not generally motivated by the possibility to reduce labour costs, but by the desire to improve the quality of products and services (Dixon et al., 2019).

pre-defined rules; on the contrary, occupations that require interpersonal and manual skills are not impacted (Webb, 2019). Finally, artificial intelligence favours an increase in employment growth for high-income occupations, while low- and middle-income occupations are not affected (Felten et al., 2019). Similarly, artificial intelligence increases non-routine work (low-skill or high-skill occupations) while decreasing routine work (middle-skill occupations); however, when artificial intelligence is combined with other technologies, even high-skill occupations may suffer a reduction (Tschang and Almirall, 2021). The adoption of artificial intelligence leads to the dismissal of production (low-skilled) workers and the hiring of tech (high-skilled) workers and the intensity of this impact increases over time (Xie et al., 2021). Occupations that are least exposed to artificial intelligence involve reasoning about complex situations, interpersonal skills, and non-routine manual work (Webb, 2019).

In general, only a few occupations seem to be affected by automation technologies; these occupations will experience a small job loss, but a higher number of jobs is expected to emerge in the economy (Vermeulen et al., 2018). Occupations that are most exposed to automation technologies regard office and administrative support, production, and delivery occupations; instead, the least exposed occupations are those in healthcare, management, architecture and engineering, academia, and art. In general, low- and medium-skilled occupations are declining, while high-skill occupations are increasing; however, even some low- and medium-skilled occupations are growing (Vermeulen et al., 2018).

3.2.10. Worker level

3.2.10.1. Probability of automation. The risk of substitution faced by workers is different depending on their characteristics (Zhou et al., 2020) such as gender, age, race, education, skills, income, type of contract, tenure, and training. Appendix D offers a summary of the evidence concerning these characteristics.

The effect of *gender* on the risk of substitution depends on the context and three cases are possible: men workers face a greater risk (e.g., Bannò et al., 2021; Mason, 2021; Pajarinen et al., 2015; Vitáloš, 2019), women workers are more at risk (e.g., Egana-delSol et al., 2021; Haiss et al., 2021; Lima et al., 2021; Zhou et al., 2020), or they face a nearly identical risk (David, 2017; Frenette and Frank, 2020; Illéssy et al., 2021; Pajarinen et al., 2015). At the European level, men workers are more at risk as they tend to be employed in occupations with a higher probability of automation and perform automatable tasks (Pouliakas, 2018). In ASEAN-5 and Singapore, this condition regards women workers (Chang and Huynh, 2016; Fuei, 2017). In OECD countries, women workers, despite being employed in occupations with a lower probability of automation, perform many automatable tasks and thus face a higher risk (Nedelkoska and Quintini, 2018).

Between *age* and the probability of automation, five types of relationships have been identified depending on the context: a negative relationship (Caravella and Menghini, 2018; Egana-delSol et al., 2021; Lima et al., 2021); a positive relationship (Fuei, 2017; Zhou et al., 2020); a U-shaped relationship (Frenette and Frank, 2020; Nedelkoska and Quintini, 2018; Pouliakas, 2018); no relationship (Yamashita and Cummins, 2021).

As regards the *race* of the worker, in South Africa, the largest portions of black, coloured, and Indian workers face a high risk of substitution while white workers face a lower risk, despite four of the largest occupations among white workers having a high probability of automation (le Roux, 2018). In the United States, occupations with a high density of racial minority men are least complementary to automation and will experience lower future labour demand (Mason, 2021).

The impact of *education* on the probability of automation is negative (e.g., Frey and Osborne, 2017; Fuei, 2017; Nedelkoska and Quintini, 2018; Pajarinen et al., 2015; Pouliakas, 2018). Lower levels of education (generally, illiterate, primary school, and middle school) are associated with a higher probability of automation, while higher levels of education (generally, professional training, high school, college and above education) with a lower probability of automation (Arntz et al., 2016; Caravella and Menghini, 2018; Chang and Huynh, 2016; Zhou et al., 2020). The difference in the risk of substitution depending on the level of education may be significant, as occurs in Brazil, Canada, China, Hungary, and South America (Egana-delSol et al., 2021; Frenette and Frank, 2020; Illéssy et al., 2021; Lima et al., 2021; Zhou et al., 2020).

As for education, *skills* are essential to reduce the risk of substitution. Workers that are most at risk are the least skilled ones (Minian and Martinez Monroy, 2018; Pajarinen and Rouvinen, 2014) and are more likely to have skill gaps in digital skills and generic skills (e.g., communication, customer-service, planning, problem-solving, and team working) (Pouliakas, 2018). Josten and Lordan (2020) confirm the importance of generic skills. On the contrary, workers with a proficiency level in literacy and numeracy and with technical skills face a lower risk of substitution (Frenette and Frank, 2020; Pouliakas, 2018). The effect of specific skills in increasing or reducing the risk of substitution faced by the worker may depend on its gender: in South America, skills regarding management, communication, self-organisation and ICT reduce the risk of substitution faced by men, while readiness to learn and creativity are more effective in decreasing the risk for women (Egana-delSol et al., 2021).

A negative relationship between *salary*, which is linked to education and skills, and the risk of substitution has been found in many contexts (e.g., Frey and Osborne, 2017; Lima et al., 2021; Nedelkoska and Quintini, 2018; Pajarinen et al., 2015; Pajarinen and Rouvinen, 2014; Pouliakas, 2018). Low-wage workers face a higher risk of substitution (Arntz et al., 2016; Haldane, 2015). The difference in the risk of substitution depending on the income may be significant, as occurs in Canada and China (Frenette and Frank, 2020; Zhou et al., 2020).

The *type of contract* affects the risk of substitution in different ways depending on the context: in OECD countries, Canada, Japan and Mexico workers with an apprenticeship, temporary or part-time contracts face a higher risk of substitution (David, 2017; Frenette and Frank, 2020; Nedelkoska and Quintini, 2018); instead, in European countries and the United Kingdom workers with a permanent contract are more at risk (McGuinness et al., 2021; Pouliakas, 2018). Self-employment or own-account increases the risk of substitution compared to wage-employment (Chang and Huynh, 2016). After considering the effect of age, longer *tenures* with the current employer increase the risk of substitution faced (Pouliakas, 2018).

Workers at high risk of substitution tend not to have done any type of *training* (on-the-job, off-the-job, informal), *formal education* or *distant learning* in the last year (Nedelkoska and Quintini, 2018; Pouliakas, 2018). These workers are on average three times less likely to have participated in these types of education (Nedelkoska and Quintini, 2018).

Other factors have been examined marginally in the literature. The *situation before the current job* affects the risk of substitution: workers who were unemployed before starting the current job tend to face a higher risk (Pouliakas, 2018).

European workers at high risk of substitution have not experienced an *improvement in their role and tasks* recently, have lower *job satisfaction*, perceive a higher likelihood of *job insecurity or job loss*, fear that their *skills* will become outdated soon, and have limited *prospects of promotion* (McGuinness et al., 2021; Pouliakas, 2018). Workers at high risk also have a *shorter working week*, by one day on average (Nedelkoska and Quintini, 2018).[7]

3.2.10.2. Net impact. According to a few studies, automation has a positive impact on all workers: the positive effects, while being more pronounced for high-skilled workers, also regard low-skilled workers (Aghion et al., 2020b; Koch et al., 2019). This result is confirmed by Klenert et al. (2020), according to which industrial robots do not negatively affect low-skill workers. Workers employed in manufacturing establishments also obtain positive effects (Koch et al., 2019).

However, most studies conclude that automation technologies have a different impact on workers depending on their socio-demographic characteristics. Worker categories that are more exposed to automation include less-educated workers[8] (Aghion et al., 2020a; Balsmeier and Woerter, 2019; Blanas et al., 2019; Borjas and Freeman, 2019; Chiacchio et al., 2018; Graetz and Michaels, 2018; Jung and Lim, 2020; Vermeulen et al., 2018), young workers (Blanas et al., 2019; Chiacchio et al., 2018), women workers[9] (Blanas et al., 2019; Borjas and Freeman, 2019), and workers employed in more automatable occupations (Borjas and Freeman, 2019; Faber, 2020). This negative effect is registered especially in manufacturing industries (Blanas et al., 2019; Faber, 2020).

On the contrary, worker categories that are less exposed to automation and, in some cases face a higher demand, include more educated workers (Aghion et al., 2020a; Balsmeier and Woerter, 2019; Blanas et al., 2019; Bonfiglioli et al., 2020; Fu et al., 2021; Stapleton and Webb, 2020; Tang et al., 2021; Vermeulen et al., 2018), older workers (Blanas et al., 2019), and men workers (Blanas et al., 2019). This increase occurs especially in service industries (Blanas et al., 2019).

In addition to the socio-demographic characteristics, some studies consider whether the worker is incumbent and regular. In the manufacturing sector, introducing industrial robots does not increase the risk of substitution faced by incumbent workers (Dauth et al., 2017, 2018). These workers usually remain with their original employer and sometimes change their occupations and tasks (Dauth et al., 2017, 2018). Incumbent workers also experience a small increase in employment (and in some cases even in wages) thanks to the long relationship with the firm (Dottori, 2021). Instead, young entrants suffer job destruction, with fewer jobs available for them (Dauth et al., 2017, 2018). Robot adoption also affect regular workers (Stapleton and Webb, 2020).

3.2.11. Work activities level

3.2.11.1. Probability of automation. Technology can now perform many tasks, not only routine ones; however, the automation potential for non-routine work activities remains limited (van der Zande et al., 2019).

45 % of the work activities that workers perform can be automated by adapting existing technologies and an additional 13 % could be automated if the technologies designed to understand natural language reached a median level of human performance (Chui et al., 2015).

More in detail, work activities that are most susceptible to automation involve physical work or operating machinery in a predictable (i.e., highly structured) environment (probability of automation equal to 78 %), data processing (69 %), and data collection (64 %) (Chui et al., 2016; Manyika, 2017). These activities are frequent in the manufacturing, accommodation and food service, and retail trade sectors (Manyika, 2017).

Work activities that have a medium probability of automation include interaction with stakeholders (probability of automation equal to 20 %) and unpredictable physical work (25 %[10]) (Chui et al., 2016; Manyika, 2017).

Finally, work activities that are least susceptible to automation include the management and development of people (probability of automation equal to 9 %) and the application of expertise to decision making, planning, and creative tasks (18 %) (Chui et al., 2016; Manyika, 2017). These activities require perception and manipulation, creative intelligence, and social intelligence (e.g., sensing emotions) (Chui et al., 2015; Frey and Osborne, 2017; van der Zande et al., 2019).[11]

4. Concluding remarks

The main evidence, organised by level of analysis and by how the impact of automation technologies on employment is estimated, is shown in Table 4.

From this review, it emerges that the literature investigating how automation technologies affect employment is extremely complex, uncertain and immature. The complexity is because publications investigate many levels of analysis, apply different approaches to assessing the impact and consider different automation technologies and because the results are extremely detailed. Moreover, the results are often inconsistent, creating uncertainty in the literature. Even publications that are similar in approach, level of analysis and technology produce opposite results and clear and irrefutable results are few.

While according to some authors, automation can increase labour demand (Aghion et al., 2020b), other authors observe that it will continue to disrupt labour markets in the future (Borjas and Freeman, 2019). However, it is emphasised that the possibility to introduce automation technologies for the performance of certain work activities does not necessarily imply a job loss for several reasons (Arntz et al., 2016).

First, various factors mitigate the speed and scope of automation adoption and thus the negative effects of unregulated technological progress: commercial availability, labour costs, labour regulation, price of capital, social preferences for human workers, and political activism (Frey and Osborne, 2017; Kim et al., 2017; Nedelkoska and Quintini, 2018; van der Zande et al., 2019). Specifically, the shortage of cheap labour encourages automation, while the high price of capital, political activism, regulatory concerns and ethical aspects hinder it (Frey and Osborne, 2017; van der Zande et al., 2019).

Second, workers can adjust to technological change (thus protecting themselves from displacement) by acquiring new skills and switching work activities (Arntz et al., 2016).

Third, technological change generates labour demand through the demand for new technologies and higher competitiveness (Arntz et al., 2016).

[7] The situation of European workers experiencing skills-displacing technological change has also been examined. These workers usually have these characteristics: are employed in high-skill occupations, perform non-routine work activities, face great job-skill requirements and dynamic upskilling, experience an increasing task variety over their tenure, work in teams, receive on-the-job training, and have been promoted by their current employer (McGuinness et al., 2021).

[8] According to other studies the impact is positive also for low-skilled workers (in addition to high-skilled workers); only middle-skilled workers suffer a reduction (Dixon et al., 2021). On the contrary, other studies find that low-skilled workers are not affected by robot adoption because they cannot be substituted in many labour-intensive firms (Stapleton and Webb, 2020; Tang et al., 2021). Instead, according to other studies, workers with a degree and those without it are affected in the same way (Aubert-Tarby et al., 2018).

[9] On the contrary, other studies note that the negative effect is (slightly) stronger for men than for women (Chiacchio et al., 2018; Faber, 2020; Fu et al., 2021). Finally, other studies find that men and women workers are affected in the same way (Aubert-Tarby et al., 2018).

[10] The potential for automation would be 67 % if technology advanced to “handle unpredictable environments with the same ease as predictable ones” (Chui et al., 2016).

[11] Capabilities such as creativity and sensing emotions are required at a median human level of performance by just 4 % of work activities as regards creativity and by 29 % as regards sensing emotion (Chui et al., 2015).

Table 4
Summary of main previous evidence.

Level of analysis	Publications estimating the probability of automation	Publications estimating the net impact on employment
Global level	49 % of the global work activities can be automated (Manyika, 2017)	*Not analysed level*
International level	21 OECD countries: 9 % of jobs are automatable (Arntz et al., 2016)	*Not analysed level*
Continental level	Europe: 54 % of workers are at risk of substitution applying the occupation-based approach (Bowles, 2014); 13.9 % applying the task-based approach (Pouliakas, 2018)	*Not analysed level*
Country level	Substantial national differences in the distributions of workers based on the risk of substitution (e.g., Manyika, 2017) Explanatory factors: type of approach adopted, industrial and labour market structure, workplace organisation, past investment into automation, education of workers (e.g., Foster-McGregor et al., 2021)	The impact of automation technologies is not clear: + Automation technologies in the long run (Autor and Salomons, 2018); Industrial robots in developed countries (Fu et al., 2021) − Industrial robots worldwide (Carbonero et al. (2018) ? Automation technologies (e.g., Fu et al., 2021); Artificial intelligence (Mutascu, 2021) 0 Industrial robots (Focacci, 2021)
Regional level	Significant variation in the probability of automation of European regions (Crowley et al., 2021) Explanatory factors: occupational structure, level of unemployment, level of development, industrial diversity, population density (e.g., Crowley et al., 2021)	The impact of automation technologies is not clear: + Industrial robots in regions (e.g., Leigh et al., 2020); Artificial intelligence for middle-skilled workers in manufacturing firms (Xie et al., 2021) − Industrial robots in communing or employment zones (e.g., Acemoglu and Restrepo, 2020); Artificial intelligence for low-skilled workers (Xie et al., 2021)
Labour market	*Not analysed level*	The impact of automation technologies is not clear: + Automation technologies (e.g., Koch et al., 2019) − Industrial robots (e.g., Chiacchio et al., 2018), only in the short run (Du and Wei, 2021), only in the manufacturing sector (Dottori, 2021) ? Industrial robots (Antón et al., 2020) 0 Industrial robots only change the composition of employment (e.g., Caselli et al., 2021; Dauth et al., 2017)
Industry level	Considerable differences across industries and across countries (Chang and Huynh, 2016) Most exposed industries: agriculture, manufacturing, construction, trade, transport, accommodation and food services (e.g., Lima et al., 2021) Least exposed industries: education, health, arts, management, public administration, public utility services (e.g., Caravella and Menghini, 2018)	The impact of automation technologies is not clear: + Automation technologies (e.g., Klenert et al., 2020), only in industries exposed to international trade and competition (Aghion et al., 2020b) and in service industries, "making" sectors and complementary sectors (e.g., Mann and Püttmann, 2018); Industrial robots (Klenert et al., 2020); Artificial intelligence in medium-tech industries (Xie et al., 2021) − Automation technologies in the manufacturing sector and in "applying" sectors (e.g., Mann and Püttmann, 2018); Industrial robots (e.g., Acemoglu et al., 2020b) 0 Automation technologies only change work organisations (e.g., Boavida and Candeias, 2021); Artificial intelligence (Acemoglu et al., 2020a)
Firm level	+ Employment in the private sector (McGuinness et al., 2021) ? Firm size (e.g., Frenette and Frank, 2020)	The impact of automation technologies is not clear: + Automation technologies (e.g.; Bessen et al., 2020); Industrial robots (e.g., Acemoglu et al., 2020b); Information technologies (Bessen and Righi, 2019) − Industrial robots (e.g., Ballestar et al., 2021) ? Industrial robots: their impact depends on firm characteristics: adopting firm or not, firm size, capital- or labour-intensive firm (e.g., Koch et al., 2019; Ni and Obashi, 2021) 0 Automation technologies (e.g., Parschau and Hauge, 2020)
Occupational level	Occupations with a high probability of automation: ▪ Many automatable tasks (e.g., exchange of information, selling, use of hands) (e.g., Arntz et al., 2016) ▪ Examples: clerks, shop assistants, cleaners Occupations with a low probability of automation: ▪ Many non-routine work activities requiring e.g., perception and manipulation, analytic thinking, creativity, social intelligence (e.g., Arntz et al., 2016) ▪ Examples: managers, hairdressers, nurses	The impact of automation technologies is not clear: + Industrial robots, for non-routine employment (e.g., de Vries et al., 2020); Artificial intelligence, for high-income occupations (Felten et al., 2019) and non-routine work (Tschang and Almirall, 2021) − Industrial robots, for routine employment (e.g., de Vries et al., 2020) 0 Industrial robots (Caselli et al., 2021); Artificial intelligence (Acemoglu et al., 2020a) Most exposed occupations: office and administrative support, production, and delivery occupations (Vermeulen et al., 2018) Least exposed occupations: healthcare, management, architecture and engineering, academia, and art (Vermeulen et al., 2018)
Worker level	+ Tenure, previous unemployment, demotivation (e.g., Pouliakas, 2018) − Education, skills, salary, training (e.g., Frey and Osborne, 2017) ? Gender, age, race, type of contract (e.g., Pouliakas, 2018)	Most exposed workers: less-educated, young, women, and employed in more automatable occupations, especially in manufacturing industries (e.g., Blanas et al., 2019) Less exposed workers: more educated, older workers and men, especially in service industries (e.g., Blanas et al., 2019)
Work activities level	45 % of the tasks can be automated (Chui et al., 2015) Most automatable tasks: physical work in predictable environments, data processing, and data collection (e.g., Manyika, 2017) Least automatable work activities: management and development of people, application of expertise to decision making, planning, and creative tasks (e.g., Manyika, 2017)	*Not analysed level*

Fourth, new occupations will emerge in the future and provide employment opportunities (Kim et al., 2017).[12]

Finally, the presence of technical limitations to total automation will reduce the negative consequences of automation in the future (Frey and Osborne, 2017). After the automation of occupations that can already be automated, there will be a slowdown in computerisation due to the presence of technical limitations to total automation (Frey and Osborne, 2017). Overcoming the limitations regarding creative and social intelligence will enable the automation of occupations that now seem to be more protected (Frey and Osborne, 2017).

Despite the uncertainty about the impact of automation, it is clear that technology is advancing very fast and affecting the workplace: while automation may lead to unemployment in the short term, it is less likely that it will cause unemployment in the long run (van der Zande et al., 2019).

4.1. Managerial and policy implications

Managerial and policy implications can be derived from this review. As regards managerial implications, firms can understand the impact that automation technologies have on their employment and workforce composition. Predictions about the future level of employment can be based on some aspects such as industry, firm characteristics, prevalent occupations and workers' characteristics. Firms can also identify the categories of workers who face a higher risk of substitution following automation. Based on this information, firms can intervene in the workplace to protect their workers. A reorganisation of work activities or the promotion of training or lifelong learning can be two feasible and effective solutions.

Policy implications can also be derived from this review. The role of public policies in influencing the effects of automation technologies on employment has been recognized in the literature (Aghion et al., 2020a). Based on the results of this review, public policies can be designed with three main objectives: promote the invention and application of automation technologies as they can be a source of firm competitive advantage (Acemoglu et al., 2020b); support firms in the introduction of these technologies by helping them carefully evaluate the consequences of automation especially concerning employment; safeguard workers that may be negatively affected by automation.

4.2. Future research agenda

Based on the results of this review, a future research agenda is offered.

4.2.1. Methodological and empirical issues

Suggestions regarding methodological issues are offered by distinguishing how the impact of automation technologies is assessed.

Publications estimating the probability of automation applying the occupation-based approach are almost exclusively based on the study by Frey and Osborne (2017). Specifically, while some studies follow the methodology proposed by these authors, others rely on their results. The first important consideration is that the results by Frey and Osborne (2017) for American occupations should not be directly applied to employment data of other countries. This is because the industrial and employment structure of each country have to be considered and occupations are not similar in different countries (Arntz et al., 2016; David, 2017). Instead, the methodology proposed by Frey and Osborne (2017) may be followed, ideally also carrying out a preliminary assessment of the probability of automation of occupations in the analysed country taking into account the structure of employment and the degree of technology diffusion. Only in this way is it possible to estimate automation probabilities that are as realistic as possible. Instead, publications estimating the probability of automation applying the task-based approach apply different methodologies and none predominates. Future studies could compare the results from the application of the main proposed methodologies and converge towards the one that seems to offer the most reliable results or eventually devise a new methodology that takes into account the strengths of the main proposed methodologies.

As regards publications estimating the net impact on employment, almost all are based on quantitative methods. Future publications should employ, in addition to quantitative methods, both qualitative and mixed methods to improve the understanding of the impact of automation technologies. These methods would enable a detailed and comprehensive investigation of the issue that quantitative methods alone cannot provide thus helping to clarify conflicting results that have emerged to date.

4.2.2. Thematic issues

Suggestions regarding thematic issues are offered considering the level of analysis and, when relevant, how the impact of automation technologies is assessed.

4.2.2.1. Global and international level. More analyses estimating the probability of automation or the net impact on employment are necessary to understand the impact of automation technologies at the global level and to detect if some geographical areas are more adversely affected than others. Further analyses should focus on geographical areas of various continents and compare countries with different characteristics (e.g., level of development and structure of the economy). The aim is to examine the differences between groups of homogeneous countries (e.g., advanced European countries) instead of differences across individual countries. Only in this way is it possible to understand whether there are factors that can be identified with respect to similar countries that do not disperse the interpretation on individual countries.

4.2.2.2. Continental level. Europe is the only continent that has been analysed in the literature but only in terms of the probability of automation. Further analyses estimating either the probability of automation or the net impact on employment are therefore necessary and should focus mainly on continents other than Europe as they have different characteristics (e.g., level of development, diffusion of automation technologies, labour legislation, labour market characteristics).

4.2.2.3. Country level. Publications assessing the probability of automation at the country level are well geographically distributed. Moreover, several factors have been identified that could explain cross-country differences in the probability of automation: the type of approach adopted (i.e., occupation-based or task-based approach), the industrial and labour market structure of the countries, workplace organisation, past investment into automation technologies, and the level of education of workers. However, there are still few studies that estimate the contribution and analyse the importance of these factors. Further analyses are desirable to help governments take action on key factors that help reduce the probability of automation in their country and, in turn, mitigate any negative impact of automation technologies on employment.

As regards the estimation of the net impact on employment, previous publications have not clearly defined what the impact is thus highlighting the need for further investigations. In addition, the effect of automation technologies other than industrial robots should be further examined. Finally, countries with very different characteristics regarding for example labour market regulations, the legal system, and fiscal policies should be considered. In this way, the specific characteristics of each country are taken into account and the macro-distinction

[12] Some authors note that even for existing occupations that have a high probability of automation the number of workers is expected to increase, as has happened in the past (Albuquerque et al., 2019).

between developed and developing countries is overcome.

4.2.2.4. Regional level. At the regional level, future studies estimating the probability of automation should consider new contexts, while those estimating the net impact on employment should try to analyse the impact of all types of automation technologies and try to clarify their effect.

In both cases, the factors that account for differences between regions in the impact of automation technologies should be further investigated. Within-country analyses may be employed to highlight the different expectations on the role of automation in each area and control for the potential effects of cross-country differences.

4.2.2.5. Labour market level. Similar to the regional level, further analyses estimating the net impact on employment are needed to clarify the impact of automation also distinguishing the type of technology and identifying the factors that explain the different effects of automation on labour markets with different characteristics.

4.2.2.6. Industry level. As regards studies estimating the probability of automation, the factors explaining the different probabilities of automation of the same industries but in different countries should be further investigated. There are only preliminary indications of such factors, which are, however, advanced in analyses at the country level.

Concerning studies estimating the net impact on employment, the impact remains unclear despite there are many analyses that focus on all types of automation technologies. Future analyses should clarify the impact, also considering industries with different characteristics arising from technological, production and engineering aspects.

4.2.2.7. Firm level. Future analyses should try to evaluate how the probability of automation varies depending on firm characteristics that have not been considered yet (e.g., firm structure such as family firm, multinational) or that have been little explored (i.e., firm dimension and private sector). Specifically, firm structure might influence the adoption of automation technologies. For instance, in family firms, the desire to preserve the socio-emotional wealth and the close relationship with employees might discourage the adoption of automation technologies. Instead, multinational firms, which operate in countries with different degrees of technological development, could have access to detailed information on the most advanced automation technologies and promote their adoption even in technologically lagging countries.

Future studies estimating the net impact on employment should try to clarify the impact of automation technologies as existing studies have come to conflicting conclusions. Moreover, future studies should focus more on the plant level as the impact of automation on individual plants within a firm may differ depending on their location (especially if in different countries), size and production activity carried out.

4.2.2.8. Occupational level. Existing publications estimating the probability of automation or the net impact on employment at the occupational level agree in identifying which occupations are most impacted, with the consequence that the occupational characteristics that influence the risk of substitution and their impact are clear. However, existing publications estimating the probability of automation of occupations have produced varying estimates for different countries. Future studies should further investigate why the probability of automation varies among countries, despite some preliminary evidence that has been advanced (see e.g., the different importance of non-routine tasks across countries). This evidence could guide government and business interventions aimed at reorganizing the structure of occupations or intervening in key factors (e.g., education, skills) to reduce the risk of substitution faced by workers.

4.2.2.9. Worker level. Studies estimating the probability of automation and the net impact on employment consider different worker characteristics in their analysis. However, the results related to some characteristics (e.g., gender, age) are inconsistent, while other characteristics (e.g., type of contract, previous unemployment, work experience) have been insufficiently examined. Further analyses should focus on these aspects, eventually considering contexts (e.g., Asian, African, and American countries) that have received little attention.

4.2.2.10. Work activities level. Existing studies clearly show that routine work activities have a higher probability of automation. However, further analyses estimating the probability of automation are advisable as it helps to understand what work activities need to be focused on to safeguard workers from their risk of substitution.

Data availability

No data was used for the research described in the article.

Appendix A. Sources of selected publications, updated on 31th December 2021

Source title	Type of source	Number of selected publications
Technological Forecasting and Social Change	Journal	6
SSRN Electronic Journal	Journal	4
European Commission	Institution	3
Research Policy	Journal	3
AEA Papers and Proceedings	Conference	2
Bruegel	Editor	2
Center for Economic Studies and ifo Institute (CESifo)	Institution	2
Economics Letters	Journal	2
ETLA Brief	Journal	2
Industrial and Corporate Change	Journal	2
IZA Institute of Labor Economics	Institution	2
Journal of Business Research	Journal	2
Journal of the Japanese and International Economies	Journal	2
McKinsey Quarterly	Journal	2
National Bureau of Economic Research	Institution	2
OECD Publishing	Institution	2
Societies	Journal	2
Technology in Society	Journal	2
Academy of Management Perspectives	Journal	1
African Journal of Science, Technology, Innovation and Development	Journal	1
Applied Economics	Journal	1

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Source title	Type of source	Number of selected publications
Applied Economics Letters	Journal	1
Asian Development Bank	Institution	1
Boston University School of Law	Institution	1
Brookings Papers on Economic Activity	Journal	1
Cambridge Journal of Regions, Economy and Society	Journal	1
Centre for Economic Policy Research (CEPR)	Institution	1
China Economic Journal	Journal	1
Committee for Economic Development of Australia	Institution	1
Communications for Statistical Applications and Methods	Journal	1
Community College Journal of Research and Practice	Journal	1
Economia Politica	Journal	1
Economic Analysis and Policy	Journal	1
Economic Modelling	Journal	1
Economic Policies since the Global Financial Crisis	Book	1
Economic Policy	Journal	1
Economics of Innovation and New Technology	Journal	1
Economie et Statistique / Economics and Statistics	Journal	1
EDAMBA 2019	Conference	1
Empirica	Journal	1
Employee Relations: The International Journal	Journal	1
Federal Reserve Bank of Minneapolis - Opportunity and Inclusive Growth Institute	Institution	1
Futures	Journal	1
Geoforum	Journal	1
Handbook of Labor, Human Resources and Population Economics	Book	1
IAB Institute for Employment Research	Institution	1
ING DiBa	Institution	1
International Economics	Journal	1
International Labour Office (ILO)	Institution	1
International Labour Office Bureau for Employers Activities Regional Office for Asia and the Pacific	Institution	1
Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP)	Institution	1
Japan and the World Economy	Journal	1
Journal of Innovation & Knowledge	Journal	1
Journal of International Economics	Journal	1
Journal of International Studies	Journal	1
Journal of Political Economy	Journal	1
Journal of Property Investment & Finance	Journal	1
Labour Economics	Journal	1
Latin American Business Review	Journal	1
L'industria	Journal	1
Management Science	Journal	1
McKinsey Global Institute	Institution	1
NYU Stern School of Business	Institution	1
Princeton University	Institution	1
Problemas del Desarrollo. Revista Latinoamericana de Economía	Journal	1
Regional Studies	Journal	1
Review of Black Political Economy	Journal	1
Southeast Asian Economies	Journal	1
Southeast Asian Journal of Economics	Journal	1
Statistics Canada = Statistique Canada	Institution	1
Stato e mercato	Journal	1
Sustainability	Journal	1
The digital transformation of labor: Automation, the gig economy and welfare	Book	1
The Review of Economics and Statistics	Journal	1
Trades Union Congress	Conference	1
Voprosy Ekonomiki	Journal	1

Source: Our elaboration.

Appendix B. Selected publications and their methodology, updated on 31th December 2021

Publication	Publication estimating the probability of automation	Publication estimating the net impact on employment
Acemoglu and Restrepo (2020)		X
Acemoglu et al. (2020a)		X
Acemoglu et al., 2020b		X
Adamczyk et al. (2021)	X	
Aghion et al., 2020a		X
Aghion et al., 2020b		X
Albuquerque et al. (2019)	X	
Antón et al. (2020)		X
Arntz et al. (2016)	X	
Asian Development Bank (2015)	X	
Aubert-Tarby et al. (2018)		X
Autor and Salomons (2018)		X

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Publication	Publication estimating the probability of automation	Publication estimating the net impact on employment
Baddeley (2017)		X
Ballestar et al. (2020)		X
Ballestar et al. (2021)		X
Balsmeier and Woerter (2019)		X
Bannò et al. (2021)	X	
Bessen and Righi (2019)		X
Bessen et al. (2020)		X
Blanas et al. (2019)		X
Boavida and Candeias (2021)		X
Bonfiglioli et al. (2020)		X
Borjas and Freeman (2019)		X
Bowles (2014)	X	
Brzeski and Burk (2015)	X	
Camiña et al. (2020)		X
Caravella and Menghini (2018)	X	
Carbonero et al. (2018)		X
Caselli et al. (2021)		X
Chang and Huynh (2016)	X	
Chiacchio et al. (2018)		X
Chui et al. (2015)	X	
Chui et al. (2016)	X	
Compagnucci et al. (2019)		X
Crowley et al. (2021)	X	
Dauth et al. (2017)		X
Dauth et al. (2018)		X
David (2017)	X	
de Vries et al. (2020)		X
Dekle (2020)		X
Dengler and Matthes (2018)	X	
Dixon et al. (2019)		X
Dixon et al. (2021)		X
Domini et al. (2021)		X
Dottori (2021)		X
Du and Wei (2021)		X
Durrant-Whyte et al. (2015)	X	
Egana-delSol et al. (2021)	X	
Elliott (2017)	X	
European Commission and Fraunhofer ISI (2015)		X
Faber (2020)		X
Felten et al. (2019)		X
Focacci (2021)		X
Foster-McGregor et al. (2021)	X	
Frenette and Frank (2020)	X	
Frey and Osborne (2017)	X	
Fu et al. (2021)		X
Fuei (2017)	X	
Graetz and Michaels (2018)		X
Haiss et al. (2021)	X	
Haldane (2015)	X	
Humlum (2019)		X
Illéssy et al. (2021)	X	
Jithitikulchai (2020)	X	
Josten and Lordan (2020)	X	
Jung and Lim (2020)		X
Kim et al. (2017)	X	
Klenert et al. (2020)		X
Koch et al. (2019)		X
Kromann et al. (2020)		X
Krzywdzinski (2021)		X
le Roux (2018)	X	
Lee et al. (2020)	X	
Leigh et al. (2020)		X
Lima et al. (2021)	X	
Mann and Püttmann (2018)		X
Manyika (2017)	X	
Mason (2021)	X	
McGuinness et al. (2021)	X	
Minian and Martinez Monroy (2018)	X	
Mutascu (2021)		X
Nedelkoska and Quintini (2018)	X	
Ni and Obashi (2021)		X
Pajarinen and Rouvinen (2014)	X	
Pajarinen et al. (2015)	X	
Parschau and Hauge (2020)		X
Pellegrino et al. (2017)		X
Piazolo and Dogan (2021)	X	

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Publication	Publication estimating the probability of automation	Publication estimating the net impact on employment
Pouliakas (2018)	X	
Şahin (2020)		X
Sequeira et al. (2021)		X
Stapleton and Webb (2020)		X
Tang et al. (2021)		X
Tschang and Almirall (2021)		X
van der Zande et al. (2019)	X	
Vermeulen et al. (2018)		X
Vitáloš (2019)	X	
Webb (2019)		X
Xie et al. (2021)		X
Yamashita and Cummins (2021)	X	
Zemtsov (2017)	X	
Zhou et al. (2020)	X	

Source: Our elaboration.

Appendix C. Summary of distributions of workers based on the risk of substitution in the various countries

Country	Distribution of workers based on the risk of substitution	Author
Occupation-based approach		
Asian countries	(Jobs) from 5% to 28% high risk	Asian Development Bank (2015)
Australia	41.6% low risk (<30%), 18.4% medium risk (30-70%), 39.6% high risk (>70%), 0.4% untapped	Durrant-Whyte et al. (2015)
Austria	40% high risk (> 70%)	Haiss et al. (2021)
Brazil	55.03% high risk (> 60%)	Albuquerque et al. (2019)
Brazil	22% low risk (<30%), 18% medium risk (30-70%), 60% high risk (>70%)	Lima et al. (2021)
Cambodia	11% low risk, 32% medium risk, 57% high risk	Chang and Huynh (2016)
China	35.8% at risk (unspecified level of risk), specifically 32.7% in urban areas and 39.5% in rural areas at risk In 2049, 332.6 million workers will be substituted conditionally on a high adoption rate of artificial intelligence and 200.7 million workers conditionally on a low adoption rate	Zhou et al. (2020)
Europe	From 40% range up to well over 60%. Northern EU countries less affected	Bowles (2014)
Europe	Norway is the least exposed country on average, Romania the most exposed	Crowley et al. (2021)
Finland	32% low risk (<30%), 33% medium risk (30-70%), 36% high risk (>70%)	Pajarinen and Rouvinen (2014)
Finland	35% high risk (>70%)	Pajarinen et al. (2015)
Germany	59% at risk (unspecified level of risk)	Brzeski and Burk (2015)
Germany	47.2% at risk (unspecified level of risk)	Dengler and Matthes (2018)
Hungary	44% high risk (> 70%), of which 25% higher than 90% and 13% higher than 95%	Illéssy et al. (2021)
Indonesia	9% low risk, 35% medium risk, 56% high risk	Chang and Huynh (2016)
Italy	30.2% low risk (<30%), 36.6% medium risk (31-70%), 33.2% high risk (>70%)	Bannò et al. (2021)
Italy	31.5% low risk (<30%), 21.2% medium risk (30-70%), 47.3% high risk (>70%)	Caravella and Menghini (2018)
Japan	18.977% low risk (<30%), 25.413% medium risk (30-70%), 55.611% high risk (>70%)	David (2017)
Mexico	(Jobs) 63% at risk (unspecified level of risk)	Minian and Martinez Monroy (2018)
Norway	33% high risk (>70%)	Pajarinen et al. (2015)
the Philippines	18% low risk, 33% medium risk, 49% high risk	Chang and Huynh (2016)
Singapore	2014: 29% low risk (<33%), 46% medium risk (33-66%), 25% high risk (>66%) 1991: 11% low risk (<33%), 43% medium risk (33-66%), 46% high risk (>66%) Singapore compares favourably to the European Union, the OECD average, the United Kingdom, and the United States	Fuei (2017)
Slovakia	2018: 18.6% low risk (<30%), 24.5% medium risk (30-70%), 56.9% high risk (>70%) 2013: 16.7% low risk (<30%), 24.2% medium risk (30-70%), 59.2% high risk (>70%) In the examined period, the percentage of workers in the high-risk category decreased by 2.3 percentage points. In absolute terms there was an increase in the number of workers in the high-risk category (due to an increase in total employment)	Vitáloš (2019)
South Africa	22.7% low risk (<30%), 22.0% medium risk (30-70%), 55.3% high risk (>70%)	le Roux (2018)
Thailand	15% low risk, 41% medium risk, 44% high risk	Chang and Huynh (2016)
United Kingdom	33% low risk (<33%), 28% medium risk (33-66%), 35% high risk (>66%)	Haldane (2015)
United States	33% low risk (<30%), 10% medium risk (30-70%), 47% high risk (>70%)	Frey and Osborne (2017)
United States	(Jobs) 48% at risk (unspecified level of risk)	Yamashita and Cummins (2021)
Viet Nam	12% low risk, 18% medium risk, 70% high risk	Chang and Huynh (2016)
Task-based approach		
World	(Activities that can be automated) Argentina 48%, Austria 47%, Australia 45%, Bahrain 46%, Barbados 49%, Bermuda 46%, Brazil 50%, Canada 47%, Chile 49%, China 51%, Colombia 53%, Costa Rica 52%, Cote d'Ivoire 44%, Czech Republic 52%, Egypt 49%, Ethiopia 50%, France 43%, Germany 48%, Ghana 51%, Greece 48%, India 52%, Indonesia 52%, Italy 50%, Japan 56%, Kenya 52%, Kuwait 41%, Malaysia 51%, Mexico 52%,	Manyika (2017)

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Country	Distribution of workers based on the risk of substitution	Author
	Morocco 51%, Mozambique 51%, Netherlands 45%, Nigeria 46%, Norway 42%, Oman 47%, Peru 53%, Philippines 48%, Poland 49%, Qatar 52%, Russian Federation 50%, Saudi Arabia 46%, Senegal 54%, Singapore 44%, South Africa 41%, South Korea 52%, Spain 48%, Sweden 46%, Switzerland 47%, Taiwan 53%, Tanzania 50%, Thailand 55%, Turkey 50%, United Arab Emirates 47%, United Kingdom 43%, United States 46%	
OECD countries	High risk (> 70%): Austria 12%, Belgium 7%, Canada 9%, Czech Republic 10%, Denmark 9%, Estonia 6%, Finland 7%, France 9%, Germany 12%, Ireland 8%, Italy 10%, Japan 7%, Korea 6%, Netherlands 10%, Norway 10%, Poland 7%, Slovak Republic 11%, Spain 12%, Sweden 7%, United Kingdom 10%, United States 9%	Arntz et al. (2016)
OECD countries	High risk (> 70%): Austria 16.6%, Belgium 14.0%, Canada 13.5%, Chile 21.5%, Cyprus 20.5%, Czech Republic 15.5%, Denmark 10.6%, Estonia 12.2%, Finland 7.2%, France 16.3%, Germany 18.4%, Greece 23.4%, Ireland 16.0%, Israel 16.8%, Italy 15.2%, Japan 15.0%, Korea 10.4%, Lithuania 21.0%, Netherlands 11.4%, New Zealand 10%, Northern Ireland 12.3%, Norway 5.7%, Poland 19.7%, Russian Federation 12.0%, Singapore 13.0%, Slovak Republic 33.6%, Slovenia 25.9%, Spain 21.8%, Sweden 8.0%, Turkey 16.4%, United Kingdom 11.6%, United States 10.0%	Nedelkoska and Quintini (2018)
Bolivia, Chile, Colombia, El Salvador	(Average automation risk): higher than 50% for all workers (both women and men) in all countries Risk larger for both genders in El Salvador, followed by Colombia, Bolivia for women and Chile for men In all countries considered and for both women and men, the percentage of workers in the high-risk category are larger than that in the low-risk category	Egana-delSol et al. (2021)
Canada	60.3% low risk (<30%), 29.1% medium risk (30-70%), 10.6% high risk (>70%)	Frenette and Frank (2020)
European countries	(Jobs) between 47% and 64% at risk (unspecified level of risk)	Foster-McGregor et al. (2021)
Europe	(Workers impacted by skills-displacing technological change) highest rates in Estonia (28%), Slovenia (25%), Czechia (24%), Portugal (21%) and Ireland (21%). Lowest rates (<7%) in Bulgaria, Malta, and Luxembourg	McGuinness et al. (2021)
European Union countries and the United Kingdom	The median EU worker faces a 51% risk of substitution	Pouliakas (2018)
Germany	40% low risk (<30%) of which 8% null risk, 45% medium risk (30-70%), 15% high risk (>70%) of which 0.4% 100% risk	Dengler and Matthes (2018)
Italy	26.4% low risk (<30%), 55.5% medium risk (31-70%), 18.1% high risk (>70%)	Bannò et al. (2021)
United States	(Occupations) fewer than 5% can be entirely automated. About 60% of occupations could at least 30% of their activities automated	Chui et al. (2015)
United States	(Occupations) less than 5% can be automated entirely. For about 60% of existing occupations, at least 30% of activities could be automated. Almost every occupation has partial automation potential	Manyika (2017)
Both approaches		
Russia	44% at risk (unspecified level of risk)	Zemtsov (2017)

Source: Our elaboration based on cited authors.

Appendix D. Worker characteristics and their impact on the risk of substitution

Variable	Impact	Details
Gender	Positive/Negative	Three types of relationship: • Male workers face a greater risk: European countries and the United Kingdom (Pouliakas, 2018), Italy (Bannò et al., 2021), Norway (Pajarinen et al., 2015), Slovakia (Vitáloš, 2019), and the United States (Mason, 2021) • Female workers face a greater risk: OECD countries (Nedelkoska and Quintini, 2018), Austria (Haiss et al., 2021), the ASEAN-5 (Cambodia, Indonesia, the Philippines, Thailand and Viet Nam) (Chang and Huynh, 2016), Singapore (Fuei, 2017), China (Zhou et al., 2020), South America (Bolivia, Chile, Colombia, El Salvador) (Egana-delSol et al., 2021), and Brazil (Lima et al., 2021) • Male and female workers face a nearly identical risk: Hungary (Illéssy et al., 2021), Finland (Pajarinen et al., 2015), Japan (David, 2017), Canada (Frenette and Frank, 2020)
Age	Positive/Negative/ U-Shaped/No/No clear	Five types of relationships: • Negative relationship: Italy (Caravella and Menghini, 2018), South America (Bolivia, Chile, Colombia, El Salvador) (Egana-delSol et al., 2021), Brazil (Lima et al., 2021) • Positive relationship: Singapore (Fuei, 2017), China (Zhou et al., 2020) • U-shaped relationship: European countries and the United Kingdom (Pouliakas, 2018), OECD countries (Nedelkoska and Quintini, 2018)[13], Canada (Frenette and Frank, 2020) • No relationship: United States (Yamashita and Cummins, 2021)
Race	Positive/Negative	Black, coloured, and Indian workers face a risk of substitution than white workers (le Roux, 2018) The occupations with a high density of racial minority men are least complementary to automation and will experience a lower future labour demand (Mason, 2021)
Education	Negative	OECD countries (Arntz et al., 2016; Nedelkoska and Quintini, 2018), European countries and the United Kingdom (Pouliakas, 2018), Italy (Caravella and Menghini, 2018), Finland (Pajarinen et al., 2015), Norway (Pajarinen et al., 2015), Hungary (Illéssy et al., 2021), ASEAN-5 (Chang and Huynh, 2016), Singapore (Fuei, 2017), China (Zhou et al., 2020), the United States (Frey and Osborne, 2017), Canada (Frenette and Frank, 2020), South America (Egana-delSol et al., 2021), Brazil (Lima et al., 2021)

(*continued on next page*)

[13] In OECD countries the peak in the probability of automation among young workers is more pronounced than that among adult workers (Nedelkoska and Quintini, 2018).

(*continued*)

Variable	Impact	Details
		The difference in the risk of substitution depending on the level of education may be significant (Egana-delSol et al., 2021; Frenette and Frank, 2020; Illéssy et al., 2021; Lima et al., 2021; Zhou et al., 2020)
Skills	Negative	Workers that are most at risk are the least skilled ones (Minian and Martinez Monroy, 2018; Pajarinen and Rouvinen, 2014) The effect of specific skills on the risk of substitution may depend on worker's gender (Egana-delSol et al., 2021)
Salary	Negative	Relationship found in: OECD countries (Arntz et al., 2016; Nedelkoska and Quintini, 2018), European countries and the United Kingdom (Pouliakas, 2018), the United States (Frey and Osborne, 2017), the United Kingdom (Haldane, 2015), Brazil (Lima et al., 2021), Finland (Pajarinen et al., 2015), Norway (Pajarinen et al., 2015), China (Zhou et al., 2020), Canada (Frenette and Frank, 2020) The difference in the risk of substitution depending on the income may be significant (Frenette and Frank, 2020; Zhou et al., 2020)
Type of contract	Dependent on the type of contract	Two types of relationship depending on the contract: • Workers with an apprenticeship, temporary or part-time contract face a higher risk of substitution: OECD countries (Nedelkoska and Quintini, 2018), Canada (Frenette and Frank, 2020), Japan (David, 2017) • Workers with a permanent contract are more at risk: European countries and the United Kingdom (McGuinness et al., 2021; Pouliakas, 2018) Self-employment or own-account increases the risk of substitution compared to wage-employment: ASEAN-5 (Chang and Huynh, 2016)
Tenure	Positive	It increases the risk of substitution (Pouliakas, 2018)
Training, formal education, distant learning	Positive	If not done, the risk of substitution increases (Nedelkoska and Quintini, 2018; Pouliakas, 2018)
Unemployment before current job	Positive	It increases the risk of substitution (Pouliakas, 2018)

Source: Our elaboration based on cited publication.

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